Fast inversion of hyperspectral observations using Gaussian Locally Linear Mapping

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Thématique(s) (1 ou 2) : méthodologie, atmosphère

Résumé :

Background and objective : The inversion of hyperspectral observations for atmospheric sounding using classical Levenberg-Marquardt (LM) iterative minimization [1] can quickly lead to prohibitive computation time when dealing with observational campaigns that provide a large amount of spatio-temporal data. To significantly improve computational efficiency, we propose to use the machine-learning capabilities of Bayesian inversion techniques.

Methods : We simulate noisy hyperspectral data using the 4AOP radiative transfer [2] and the real transfer function of the SCARBO instrument [3] dedicated to monitoring greenhouse gases (GHG) from space. The non-linear forward relationship Y=F(X) between hypersectral observations Y and atmospheric parameters X is modeled using the Bayesian Gaussian Locally Linear Mapping (GLiMM) approach [4], which constructs a joint probability density p(X,Y) represented by a Gaussian mixture. The model is learned from a specific training dataset covering the range of admissible atmospheric parameters. The backward model -- that is the probability of having X knowing the observations Y -- is then estimated, and the atmospheric parameters of an independent testing dataset are retrieved and compared with their true values.

Results : We show that our GliMM approach retrieves atmospheric parameters a few thousand times faster than iterative LM inversion, while providing similar estimates without significant differences. Considering a 64x64 pixel wide simulated scene with anthropogenic CO2 emission, we show that the GliMM process is able to localize the plume with the proper mixing ratio (see Fig. 1) in a few minutes at most.

Conclusion : GliMM modeling is a promising alternative for reliably estimating GHG concentration from a large hyperspectral dataset in a reasonable timeframe.

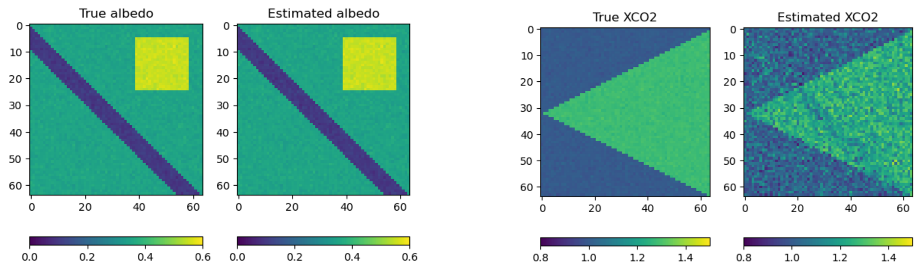

Figure 1 : Comparison of true and GliMM-estimated albedo (left) and CO2 mixing ratio (right) parameters for a simulated observation of a spatially localized CO2 plume.

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[2] Gousset, Silvère, et al. "NanoCarb hyperspectral sensor: on performance optimization and analysis for greenhouse gas monitoring from a constellation of small satellites." CEAS Space Journal 11 (2019): 507-524.

[3] Chaumat, L., et al. "4AOP: A fast and accurate operational forward radiative transfer model."

[4] Kugler, B., Forbes, F., & Douté, S. (2022). Fast Bayesian Inversion for high dimensional inverse problems. Statistics and Computing, 32(2), 31.